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Advanced Bibliometric Methods to Model the Relationship between Entry Behaviour and Networking in Emerging Technological Communities

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ADVANCED BIBLIOMETRIC METHODS TO MODEL THE RELATIONSHIP BETWEEN ENTRY BEHAVIOUR AND NETWORKING IN EMERGING TECHNOLOGICAL COMMUNITIES

ABSTRACT

Organisational ecology and social network theory are used to explain entries in technological communities. Using bibliometric data on 411 organisations in the field of plant biotechnology, we test several hypotheses that entry is not only influenced by the density of the field, but also by the structure of the R&D network within the community. The empirical findings point to the usefulness of bibliometric data in mapping change and evolution in technological communities as well as to the effects of networking on entry behaviour.

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ENTRY PATTERNS, POPULATION DENSITY AND TECHNOLOGICAL COMMUNITIES

What are the processes underlying organisational entry into new markets? As an answer to this question, organisational ecology (Hannan and Freeman, 1977&1989) has shown that the founding of organisations depends to a large extent on the number of organisations that already exist in the population of interest, i.e. the organisational density. Initially, when density is low, each founding eases subsequent foundings (Hannan, 1986 ; Hannan and Carroll, 1992), because the simple prevalence of a form tends to give it legitimacy (DiMaggio and Powell, 1983). Moreover, the training ground for qualified personnel grows (Brittain and Freeman, 1980) and the supporting networks are widened and strengthened (Garud and Van de Ven, 1989). Though, this legitimation process does not continue indefinitely. Once a treshold of organisations of a certain kind exists, the legitimation effect saturates and does not increase further (Hannan and Carroll, 1992:51).

As the number of organisations grows further, competition for limited resources becomes the prevalent environmental force, inducing a negative relationship between density and founding rates, everything else equal (Hannan and Carroll, 1992:95). Given a set of environmental conditions that sets a carrying capacity [i.e. the maximum number of organisations in a certain population that can thrive on the limited resources available (Hannan and Freeman, 1989:123-129)], the more abundant the number of competitors, the fiercer the competition will be and the lesser the incentives for new organisations to enter. Moreover, new organisations compete with established ones that have survived selectionist pressures and that are likely to fit well with the environment (Hannan and Freeman, 1977&1989). Thus, the founding rate declines as the number of organisations increases in the high density range. Both processes, legitimation and competition, lead to an inverted U-shaped relationship between population density and founding rate, called the "density-dependence model" (Hannan and Freeman, 1989).

The density-dependence model is likely to apply not only to the founding of organisations, but also to the entry of existing organisations in a new field (Wholey and Sanchez, 1991; Haveman, 1993). Although the specific processes of creation and diversification are likely to differ, Van de Ven and his colleagues (1989) showed that the core processes for the founding of a new organisation and the establishment of a new division of an existing organisation are basically the same. The decision an existing organisation faces when assessing whether or not to enter a new field is, amongst others, based on legitimative and competitive dynamics.

Moreover, it is the central thesis of this paper that the legitimation-competition dynamics underlying the density-dependence model also hold for technological communities. A technological community has been defined as the population of research organisations working on an interrelated techno-scientific problem-set, regardless whether they belong to the public or private sector (Debackere and Rappa, 1994). Our first hypothesis then aims at the extension of the density-dependence hypothesis to explain entry patterns in technological communities:

H1: The rate of entry into a technological community has an inverted U-shaped relationship with community density.

ADDING SOCIAL CAPITAL TO THE EQUATION

The density in a population is one measure that captures the legitimation and competition of a new form. We further hypothesise that, beside density, a second intra-population process is important in explaining entry patterns, i.e. the formation of networks. Networks capture relationships among organisations, in between the discrete alternatives of arm's length market transactions and hierarchies. Powell (1990:303) states: "The basic assumption of network relationships is that one party is dependent on resources controlled by another, and that there are gains to be had by the pooling of resources." Furthermore, organisations engage in relationships built on mutual trust to overcome their inability to anticipate uncertain results (Barney and Ouchi, 1986; Larson, 1992; Pisano, Shan and Teece, 1989; Thorelli, 1988). Both resource-dependency approaches (e.g. Cook, 1977; Pfeffer and Salancik, 1978; Powell, 1990; Wernerfelt, 1984) and transaction cost economics (e.g. Jarillo, 1986; Pisano, 1990; Provan, 1993; Thorelli, 1988) postulate that under the conditions of complex, indivisible resources *and* long-term goal uncertainty, network forms of organisation may be prevalent. As a consequence, an important research question becomes how the network structure as it evolves within a specific population of organisations might affect entry patterns.

Whereas population ecology stresses the primacy of environmental forces on organisational existence, social ecology points to the proactive networks that organisations build in order to cope with those forces (Astley and Fombrun, 1983; Astley, 1984; Coleman, 1988; Emery and Trist, 1973; Granovetter, 1985). Social ecology builds on the hypothesis that no single organisation possesses the necessary financial and technical capabilities to control all these forces. Therefore, co-operation offers a viable alternative to gain access to complementary assets and skills. Especially in emerging fields, incumbents perceive an urgent need for co-operation to overcome the environmental uncertainties and complexities they face (Cohen and Levinthal, 1990; Gray, 1985; Pisano, Shan & Teece, 1988).

However, the network strategy of each organisation is likely to be influenced by the evolving relational and positional network structure in the population (Barley, Freeman and Hybels, 1992). This has major implications for potential entrants. As they often lack (some of) the resources required to compete successfully in the new market, a network-like arrangement may provide the best solution to overcome entry barriers imposed by a lack of know-how, economies of scale and scope, or complementary assets (Gray, 1985). Hereby, we hypothesise that the probability of entry through co-operation will, amongst other factors, be determined by the network structure already present among the incumbent organisations. More specific, entry barriers will depend on the degree to which strong cliques are present among the incumbents.

Burt (1980) operationalises a clique as "a set of actors in a network who are connected to one another by strong relations" (p. 97). Strong cliques develop because network partners have to invest considerable amounts of time and energy in developing a viable network arrangement (e.g. Larson, 1992; Snow, Miles and Coleman, 1992; Powell, 1990). Once a strong clique has developed, the stable relationship that occurs among members of the clique will decrease opportunities for new entrants to engage in collaborations with the incumbents. Or, just as Granovetter states that "no strong tie is a bridge" (1973:1364), we hypothesise that "no strong clique can act as a bridge" to sustain entry into a population.

This is because members of a strong clique will have a tendency to restrict partnering to organisations that can contribute significantly to their network goals. As a consequence, only those organisations which possess legitimacy or prestige in the population will face opportunities to engage in network-like arrangements with incumbents already belonging to a strong clique. But legitimacy and prestige are precisely the two elements which most potential entrants lack. As a consequence, it will be more difficult for a potential entrant to establish a link with an incumbent if this incumbent already belongs to a strong clique. This in turn may increase entry barriers. Hence, the hypothesis:

H2: The ratio of organisations participating in strongly connected networks to the total number of organisations in the population or community will negatively affect the entry rate of new organisations.

Many researchers further agree that the actions of prestigious organisations influence the actions of other organisations in a market (Burns and Wholey, 1993; Haveman, 1993:598). However, much less consensus exists on what "prestige" is or how it can be measured. Both size and profitability have been used as proxies for organisational prestige (Dimaggio and Powell, 1983; Haveman, 1993). Size stands for visibility and "visible" organisations receive a great deal of prestige (Scott, 1992). Profitability is a reflection of success, which in turn is one of the building blocks of prestige (Burns and Wholey, 1993). However, in emerging industries neither size nor profitability of the incumbents are stable or transparent. Therefore they may not be suitable indicators of prestige. What then determines organisational prestige and even more important, how can it be measured?

Obviously, prestige is a multi-dimensional construct with the relative importance of its components differing according to the market or industry studied. In plant biotechnology, for instance, prestige is related to technical expertise and experience. Hence, we assume that prestigious organisations have superior knowledge of their (industrial) environment. Social network theory then offers an interesting avenue to operationalise prestige.

Social network research has shown that organisations that have a thorough understanding of their environment also occupy a central place in their respective industry networks (Bonacich, 1987; Davis, 1991; Freeman and Barley, 1990). Centrality provides access to information that flows through the network (Useem, 1984). As a consequence, Davis (1991:592) concludes: "By maintaining ties to a large number of other organisations, more central firms are able to notice and respond to environmental changes more rapidly....in addition, centrality indicates a firm's status and the degree to which it is integrated into the corporate elite." Hence, network centrality provides a valid operationalisation of the prestige construct.

How then does the dispersion of prestige throughout the industry affect the rate of entry? More precisely, is a network structure where prestige is concentrated among a few organisations more favourable to potential entrants than a structure where prestige is rather equally spread across incumbents? DiMaggio and Powell (1983) emphasise the role of prestigious organisations in attracting new entrants. As potential entrants often face considerable "searching costs," they will tend to evaluate the overall attractiveness of an industry against the prestige position of a limited number of organisations. Hence, the prestige of this small elite influences the perceived prestige of the total domain.

When prestige is more or less equally spread across incumbents, no highly visible corporate elite of prestigious organisations exists. The network structure is fragmented and the appeal to potential entrants to mimic prestigious incumbents is hence minimal. In plant biotechnology for instance, the prestige of the research groups affiliated with the Universities of Gent

(Belgium), Leiden (The Netherlands) and the Max Planck Institute (Cologne) in the early 1980s, attracted many new entrants. Some of them, such as Plant Genetic Systems (Gent) and Mogen (Leiden) have now themselves become leading organisations. Hence the hypothesis:

H3: The concentration of prestige among the incumbents will positively influence the rate of entry in an emerging population or community.

RESEARCH SITE

The research site considered is the plant biotechnology research community. This field is a sub-domain of biotechnology in which the technique of genetic engineering is applied to plant varieties. Interest in plant quality improvement was first aroused in the 1950s as a result of research into tissue cultures and the restrictions of tissue cultures. The emergence of genetic engineering in the early seventies, combined with the specification of the Tumor Inducing Plasmid (Ti-Plasmid) in 1974, caused a renewed interest in the field. In the early eighties, a collaboration between Max Planck Institute and the University of Gent resulted in the first successfully manipulated transgene plant. By now, the domain is divided into three major application areas: (1) plant crop protection, (2) plant quality improvement and (3) plant hybrids (for a review: see Grierson, 1991).

Plant crop protection aims at developing virus free plants with increased stress, herbicide or disease resistance. Plant crop quality improvement aims at the engineering of proteins with increased nutritional value, control of ripening, prolongation of shelf life, and control of flower colouring. The production of hybrid seeds implies the conversion of open pollinated varieties to hybrids in order to provide farmers with superior quality seeds. At the same time, it allows seed companies to protect the value they create through research and breeding. The first commercial products in all areas are predicted in the period 1994-1996. Thus, between the early 1980s and 1994, transgene plants have moved from a scientific curiosity to a promising commercial activity.

MODEL SPECIFICATION

When modelling the entry of organisations in a population, the level of analysis is the population (Hannan and Carroll, 1992:236). In our analyses, we deal with repeated events occurring to the population of interest (Allison, 1984:51). This kind of process is easily modelled as an arrival or a point process (Cox and Isham, 1980:2). The entry rate is the dependent variable in the analyses. The baseline model for comparison is always the constant rate, time-independent Poisson model [$\lambda(t)=C$], also called the exponential model (Allison, 1984:23), describing a series of events, distributed randomly across time.

In order to introduce heterogeneity into the baseline stochastic model, the entry rate is specified as a function of explanatory variables, $\lambda(t)=\log(\beta x)$, where x is a vector of co-variates and β the vector of parameters to be estimated, showing the effects of the co-variates (Tuma and Hannan, 1984: chapter 6). The log-linear form is preferred because it assures that all predicted rates will be nonnegative.[1] More explicitly, the full model in our analyses is as follows:

$$\lambda(t)=\exp(\alpha_1 \text{Density}_t+\alpha_2 \text{Density}_t^{\,2}+\alpha_3 \text{CliqueRatio}_t+\alpha_4 \text{Concentration}_t)\ \exp(\beta x)$$

Hypothesis 1 requires that $\alpha_1>0$ and $\alpha_2<0$; hypothesis 2 that $\alpha_3<0$; and hypothesis 3 that $\alpha_4>0$ (given the variable definitions, see below).

The entry rate is estimated in discrete time (i.e. event count analysis). In event count analysis, the observation period is divided into fixed disjoint time intervals

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[1]This is a desirable characteristic, as negative entry rates are meaningless.

occurring in series and the number of events that occur in every interval are counted (King, 1988). The *counting* specification relies on the number of events in the fixed time intervals. The probability that exactly n events occur in the interval (0,t) is given by (Amburgey and Carroll, 1984:41):

$$Pr(N_t=n)=(\lambda t)^n e^{-\lambda t}/n!$$

The mean of the distribution of the number of events in a fixed interval of length t equals its variance and is λt. Violation of the assumption of equal mean and variance in the discrete time analyses causes the variances of the parameter estimates to be inconsistently estimated and hence, invalidates the hypothesis tests. In order to relax the assumption, the Negative Binomial model is estimated. This is an extension of the Poisson regression model with an additional parameter which captures the degree of overdispersion in the event rates.

The parameters are estimated with LIMDEP (Greene, 1992). We use the POISSON module. We then adopt the following approach. First, the baseline model including a set of control variables is estimated. Second, the density and density-squared are included in order to test the first hypothesis. Third, the network variables are added in order to test the second and the third hypothesis. Fourth, we check whether the Negative Binomial fits better than the Poisson model.

DATA COLLECTION

Data on the plant biotechnology population were collected via archival sources available on the activities within research communities [which can in fact be considered "markets of ideas," see below]. Research notes, journal articles and conference papers represent a detailed archival record of the research efforts performed by each organisation in the domain (Debackere et al., 1993). If an organisation publishes an article or a conference paper for the first time, this indicates that the organisation enters the research domain. Moreover, whenever two or more research organisations jointly publish an article or a conference paper, this is interpreted as the outcome of a collaborative research effort. In this way, the population of research organisations active in a certain domain and the structure of the R&D network in the population can be detected. Furthermore, operationalising the research network in this manner has major advantages: (1) as the publication conventions ensure a level of quality and authenticity, the research collaborations detected are assumed to attain a certain minimum quality threshold; (2) as the data are public, the data collection process can be easily replicated; and (3) bibliometric databases provide detailed information about the research organisations active in the domain.

We used the databases of the Institute for Scientific Information (Philadelphia, U.S.) to identify publications related to the field of transgene plants. For the period before 1982, we used the ON-LINE version. From 1982 onwards, the quarterly updated CDROM versions were available. Both databases were searched using a search strategy consisting of a Boolean combination of 18 key terms. The search strategy was verified with three independent experts. As the boundaries of a research community are fuzzy to a certain extent (Rappa and Debackere, 1992; Debackere and Rappa, 1994), we checked the completeness of the ISI databases. Therefore, we compared the ISI documents for 1990 with a sample from the biological abstracts database (provided by BIOTEST). The ISI sample contained 189 unique documents, 160 of which also appeared in the BIOTEST sample. In addition, we checked our database against a sample of 100 hardcover articles selected by one of the experts. This check revealed that 80% of the publications in the expert's sample were retrieved with the electronic search strategy.

This data collection procedure resulted in the identification of 1792 unique source documents published between 1974 and 1993. A total of 3220 researchers appeared at 411 organisations active in the field over the twenty-year period.

VARIABLES

Dependent variable

For the 411 research organisations in plant biotechnology, we computed the number of entries for each quarter during the twenty-year observation period. This resulted in 80 observation periods. In Figures 1&2 we show the number of entries and the end-of-year density during each year of observation.

— Insert Figures 1&2 about here —

Control variables

In order to capture the heterogeneity in the data-set used, a set of population-specific control variables was constructed. When the carrying capacity of the environment changes, the entry rate is also expected to change. When resources become more abundant, the carrying capacity rises, implying that the number of organisations that can thrive increases. An increased carrying capacity will thus have a positive effect on the entry or founding rate. In order to control for this effect, environmental co-variates are introduced in the models.

According to the theoretical work of Nelson and Winter (1982), Dosi (1982) and Tushman and Anderson (1986&1990), technological development is a process of technical variation, selection of a "dominant design" and retention via development of this design. It is driven by random technological breakthroughs. Furthermore, Tushman and

Anderson (1986: 615) argue that the emergence of a "dominant design" is a prerequisite to mass adoption of a new generation of technology. These insights can now be applied to the plant biotechnology population.

It was not until three pioneers (Monsanto Co., Max Planck Institute and University of Gent) succeeded in the manipulation of the first transgene plant and the construction of the first engineered gene, that plant biotechnology research aroused the interest of some major universities or established firms. At that time, the use of the agrobacterium tumefaciens related Ti-plasmid was the "dominant design" to genetically manipulate different kinds of plant varieties. Consistent with previous research, we argue that the further this technique of Ti-plasmids is elaborated, the more organisations will start to use it to manipulate plants. This should increase the carrying capacity of the environment and hence lead to an increasing number of new entrants. In order to include this effect we have constructed a variable capturing the time dimension in the data-set. We therefore assume that the date of entry, measured by the quarter of the year an organisation enters, will positively influence the rate of entry.

Research on the sociology of technology has modelled technology development as a problem solving activity which spreads throughout a community of practitioners (Rappa and Debackere, 1992). As the activity in the research field becomes more buoyant, we assume more organisations will be attracted to it. Therefore, the cumulative number of publications in the domain is computed and serves as an indicator of the level of activity. This variable is computed on a yearly basis.

Finally, research has pointed to the importance of "market-pull" forces on entry behaviour (Kamien and Schwartz, 1982). Of course, in an area like plant biotechnology research, it is difficult to think of a market as a conventional product market. However, we may assume that a market of ideas exists where research organisations attempt to stake claims at new knowledge they created (Nelson, 1990). The "market-pull" forces operating within this market of ideas can then be operationalised through the growth rate of the publication output in the field. In terms of measurement, we therefore computed the compound growth rate of the number of publications during each year of observation (i.e. the market growth variable). We hypothesise that the growth of this idea market acts as an incentive to enter the field.

Independent variables

The DENSITY and DENSITY^2/1000 variables are calculated in order to measure the density dependence of entry rates in both populations. Second, based on the co-authorship data available in the bibliometric database, a network clique ratio and a concentration index of network centralities are computed. These network variables were computed on a yearly basis.

Strongly connected networks of organisations correspond to completely connected cliques in social network theory or strong components in graph theory. Strong cliques were detected using the clique detection algorithms provided by STRUCTURE (Burt, 1991). The network clique ratio variable is then created by dividing the number of organisations in the population belonging to any completely connected clique by the total number of organisations in the population for each year of observation.

Previously, we have argued that the prestige of an organisation can be measured by its centrality in the industry network. Social network theorists, though, have defined network centrality in a number of different ways (Freeman, 1979; Freeman, Borgatti and White, 1991; Knoke and Kuklinski, 1983). Freeman et al. (1991) distinguish two major approaches to network centrality: "First there are those who view an actor as central in a social network to the extent that he or she is somehow 'close' to everyone else in the network .... the second intuition grows out of the idea that people are somehow central to the degree they stand between others on the paths of communication" (Freeman et al, 1991: 141-142).

The first approach stems from the idea that an actor who is close to the other actors in a network will have more power, more prestige and more influence than the others (Bonacich, 1987; Burt, 1991; Friedkin, 1991). The second approach views central actors as those who can facilitate or inhibit the communication of others (Freeman, 1979). Hence, they can either be a weak tie fulfilling a broker role or a strong tie possessing degree centrality (Granovetter, 1973). As we are interested in the type of centrality that enhances prestige or status in the network, we use the centrality indices that originate from the first approach. Among those indices, we have chosen the most simple one which is calculated by dividing the number of actors who reach ego by the number of actors who could have done so.[2] In addition, in order to allow for comparisons across time, we have normalized this index by using the centrality of the most central actor as denominator. Hence, the normalized centrality of each organization is the ratio of its centrality to the centrality of the most central actor.

To test hypothesis 3, we compute the entropy index as an indicator of the concentration of prestige among the different organisations in the network. The entropy

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[2]The centrality index for each actor or organisation i is computed as (Burt (1991), STRUCTURE *Reference Manual*, p. 189):

$$\Sigma_j \delta_{ij}/(N-1) \text{ with } j \neq i$$

where N is the number of organisations in the community (i.e. not just the number of organisations *connected* to i) and δ_{ij} equals 1 if j can reach i, otherwise δ_{ij} equals 0.

index[3] is generally accepted by industrial economists as a valid measure of concentration (Encaoua and Jacquemin, 1980; Tirole, 1988). The result is a variable which takes on negative values to zero; where zero points to a monopoly situation (hence the model specification that α_4 should be positive given hypothesis 3). As a consequence, the more the index approaches zero, the more prestige tends to be concentrated among a few organisations.

The descriptive statistics for these variables are shown in Table 1.

— Insert Table 1 about here —

RESULTS

As the Negative Binomial regression models do not fit the data better than the Poisson models, only the latter will be commented upon.[4]

— Insert Table 2 about here —

The first hypothesis is supported. Upon examining the second model in Table 2, a significantly better fit is observed than for the first model (χ^2=6.38, Δd.f.=2, $p<0.05$). Thus, adding the density and density squared to the baseline model including only the control variables improves the model significantly. The coefficients of the density and the density squared are in the hypothesised direction and statistically significant ($p<0.01$). This implies density has an inverted U-shaped relationship with the entry rate in the plant biotechnology population. The entry rate is maximal when there are 270 research organisations in the domain; this is just at the

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[3]The entropy index of market share concentration is defined as the sum of the shares times their logarithm:

$$\text{entropy} = \Sigma_i \alpha_i \ln \alpha_i \text{ with } i=1\ldots N$$

[4] Due to problems of convergence, the Negative Binomial model could only be estimated for 3 of the 5 models.

limit of the observed density range. Competition thus starts slowing down the entry rate, which was still rising until 1993. We may expect that the entry rate has reached its top level. Including the network variables does not affect this relationship between population density and entry rate: the coefficients of the density variables always remain statistically significant ($p<0.01$) and in the hypothesised directions.

Hypothesis 2 is supported. Adding the network clique ratio in step 3 improves the fit of the model compared to step 2 ($\chi^2=5.36$, $\Delta d.f.=1$, $p<0.05$). The coefficient of the network clique ratio is statistically significant ($p<0.05$) and negative. Including the network centrality concentration also has an effect: model 4 fits the data better than model 2 ($\chi^2=3.94$, $\Delta d.f.=1$, $p<0.05$). The coefficient of the centrality concentration variable is significant ($p<0.01$) and in the direction hypothesised.

The best fit is obtained with the fifth model, which includes the combined effect of the network clique ratio and the centrality concentration. This model fits significantly better than the fourth model ($\chi^2=7.22$, $\Delta d.f.=1$, $p<0.01$) and than the second model ($\chi^2=11.16$, $\Delta d.f.=2$, $p<0.001$). The coefficients of the network variables are statistically significant ($p<0.01$) and in the hypothesised directions.

DISCUSSION

Network forms of organisation have aroused major interest both with management scholars and practitioners. Nohria and Eccles (1992: chapter 11) describe this new organisational form as consisting of a fluid, flexible and dense pattern of working relationships that cut across various intra- and inter-organisational boundaries. The basic assumption underlying this new ideal-type of organisation structure is that there are gains to be had by the pooling of resources. This rise of the hybrid form of organisational governance (Williamson, 1991) is further explained by the fundamental change in the nature of the problems which confront both public and private sector organisations (Ackoff, 1974&1981; Schon, 1971). Many problems simply exceed the capacity of any single organisation to control.

However, as organisations try to reduce the uncertainty and the complexity of the problems they face by engaging in network-like arrangements, new issues that warrant detailed research attention arise. Indeed, just as organisational ecology, through its density-dependence approach, has been able to show how population-level variables affect founding and entry rates into specific organisational populations, we started out asking how the network structure at the population-level might possibly influence founding and entry rates. Under certain conditions, the population network structure was assumed both to inhibit or to enhance organisational entries. This issue has been the central focus of the research reported in this paper.

Besides extending, replicating and validating the density-dependence hypotheses for entry rates, we were able to provide support for the hypothesis that strong cliques act as a deterrent to enter a population. The more the organisations within a population become strongly connected, the higher the barriers to enter that population. In other words, the macro-level network pattern in the population exerts a significant influence on the micro-level phenomenon of organisational entry.

This influence might further be explained as follows. Entry is based on expectations (Baumol, 1982; Hatten and Hatten, 1987). In the plant biotechnology research community, entry is based both on expectations to contribute to knowledge development in the field and/or on expectations to capture future benefits from the market introduction of transgene plants. Hence, in this population both for-profit and not-for-profit entry motives are present. As potential entrants often lack at least some of the resources necessary to compete successfully in the new market, their ultimate survival may depend on their possibility to engage, within a short delay of their entry, into network-like arrangements with incumbents.

This avenue can then provide them with the know-how, the economies of scale and scope, or the complementary assets they lack. The argument developed in this paper suggests that this will be less likely as an increasing number of incumbents become connected in strong cliques. In other words, the degrees of freedom for a potential entrant to engage into network-like arrangements decrease as the connectedness of the population's overall network structure increases. As a consequence, entry barriers rise.

Moreover, even at the macro-level of the population network structure, the analyses reported in this paper may provide support for Granovetter's argument (1973) on the cohesive or bridging power of weak ties. When Granovetter attempted to link network structure to job searches, he found that the participants in his study almost never found a job through close contacts. And, whenever a job opportunity occurred through a personal contact, the contact was often distant. Hence, the weak tie argument. As people are involved in clusters of other people with whom they have developed strong ties, information spreads rapidly within the cluster and each person tends to know what the other people know. The diffusion of information and new ideas thus must come through the weak ties that connect people in separate clusters.

Burt has further developed the weak-tie argument: "a bridge is at once two things. It is a chasm spanned and the span itself. By title and subsequent application, the weak tie argument is about the strength of relationships that span the chasm between two social clusters. The structural hole argument is about the chasm spanned. It is the latter that generates information benefits. Whether a relationship is strong or weak, it generates information benefits when it is a bridge over a structural hole" (Burt, 1992: 28). Based on the evidence presented in this paper, we speculate that the probability for new entrants to engage in network-like arrangements will vary directly with the degree to which weak ties or "structural holes" are present in the population's network structure. In other words, the presence of structural holes in the population network creates opportunities for collaboration because they tend to reduce network cohesion.

Thus, we hypothesise that also for new entrants "the task for building an efficient-effective network is to focus resources on the maintenance of bridge ties. Otherwise, and this is the correlative substance of the weak tie argument, bridges will fall into their natural state of being weak ties" (Burt, 1992: 30). However, the possibilities for a new entrant to develop bridge ties with incumbents will be at least partly determined by the network structure already in place among the incumbents.

In addition, we found strong support for the influence of network prestige on entry behaviour. A high concentration of network prestige actually lowers entry barriers: a highly visible, prestigious organisational elite will attract potential entrants to the market or community. Thus, a high concentration of network centrality is particularly conducive to mimetic behaviour on behalf of potential entrants because it may reduce their "searching costs" when making an entry decision (Haveman, 1993).

CONCLUSION

Although the issues raised in the paper open up interesting perspectives for further research, they are believed to have immediate implications to anyone interested in the dynamics of inter-organisational networks. First of all, although we only focused on the relationships between population-level network structures and entry rates, the results stress the importance of adopting a more holistic approach towards the "networking phenomenon." Indeed, many studies have looked into the network strategies of individual organisations, thereby neglecting many of the environmental network dynamics discussed in this paper (e.g. Freeman and Barley, 1990). During our research, it has become obvious that organisation-level entry patterns may be seriously constrained by population-level network dynamics.

This finding, of course, opens up interesting alleys for further research. Indeed, given the mechanisms discussed in the previous paragraphs, we may start wondering how organisation-level network strategies are either enhanced or impeded by the population-level network structure. To be sure, in the context of this paper, we did not yet look into the interactions that exist between organisational-level network strategies and population-level network dynamics. However, the research reported here suggests that some powerful interaction effects may be at work. In our explanation of the entry barriers created by the population's overall network structure, we already alluded to the fact that connectedness actually decreases the likelihood for new entrants to engage in network-like arrangements. If the etiology of the population's network structure on entry operates along these dimensions, then it is obvious that this structure has the potential to constrain organisation-level network strategies. Unfortunately, most organisations have at best a fragmented view of the network structure in the population(s) of interest to them; let alone that they understand the threats and opportunities imposed on their own network strategy by this overall structure.

Second, in the last few years, we have seen a dramatic increase in industry-level programs to stimulate network formation. Here we refer to arrangements like SEMATECH in the US, or the ESPRIT and SPRINT programs in Europe. The results of similar schemes have often been ambiguous and even be met with disappointment both on behalf of the organisations involved as well as on behalf of the program sponsors. Based on our previous discussion, we suggest that this may be due to unrealistic expectations based on a poor understanding of population-level network dynamics as these may exert a powerful impedance effect on the development of individual network strategies.

Third, sofar we have focused on a limited set of quantitative dimensions (both relational and positional) of network structure. As yet, we still have to start unravelling the role of content and quality of the network ties examined. Though, it is obvious that adding the social capital dimension to the equation when studying organisational entry and mortality rates offers interesting perspectives for future research on organisation dynamics. Hence, including social capital variables may provide an interesting impetus to the research agenda on the evolutionary dynamics of organisations (e.g. Baum and Singh, 1994).

REFERENCES

Ackoff, R.L. (1974). Redesigning the Future. New York, NY: John Wiley & Sons.

Ackoff, R.L. (1981). Creating the Corporate Future. New York, NY: John Wiley & Sons.

Allison, Paul D. (1984). Event History Analysis : Regression for Longitudinal Event Data. Newbury Park, CA : Sage Publications.

Amburgey, Terry A. and Glenn R. Carroll. (1984). Time series models for event counts. *Social Science Research*, 13 (1):38-54.

Anderson, Philip and Michael L. Tushman (1990). Technological discontinuities and dominant designs: a cyclical model of technological change. *Administrative Science Quarterly*, 35: 604-633.

Astley, Graham W. (1984). Toward an appreciation of collective strategy. *Academy of Management Review*, 9 (3): 526-535.

Astley, Graham W. and Charles J. Fombrun (1983). Collective strategy: social ecology of organisational environments. *Academy of Management Review*, 8 (4): 576-587.

Barley, S.R., Freeman, J. and R.C. Hybels. (1992). Strategic alliances in commercial biotechnology. In N. Nohria and R.G. Eccles (eds.) Networks and Organisations. Boston, MA: Harvard Business School Press.

Barney, Jay B. and William G. Ouchi (1986). Organisational Economics. San Francisco: Jossey-Bass.

Baum, Joel A.C. and Jitendra V. Singh (eds.). (1994). Evolutionary Dynamics of Organisations. New York, NY: Oxford University Press.

Baumol, William J. (1982). Contestable markets: an uprising in the theory of industrial structure. *The American Economic Review*, 72 (1):1-15.

Bonacich, Phillip. (1987). Power and centrality: a family of measures. *American Journal of Sociology,* 92 (5): 1170-1182.

Brittain, Jack W. and John Freeman (1980). Organisational proliferation and density-dependent selection. In J.R. Kimberly and R.H. Miles (eds.) The Organisational Life Cycle: Issues in the Creation, Transformation and Decline of Organisations: 291-338. San Francisco, CA: Jossey-Bass.

Burns, Lawton R. and Douglas R. Wholey. (1993). Adoption and abandonment of matrix management programs: effects of organisational characteristics and inter-organisational networks. *Academy of Management Journal,* 36: 106-108.

Burt, Ronald S. (1980). Models of network structure. *Annual Review of Sociology*, 6: 79-141.

Burt, Ronald S. (1991). Structure Reference Manual, version 4.2. New York: Columbia University's Centre for the Social Sciences.

Burt, Ronald S. (1992). Structural Holes: The Social Structure of Competition. Cambridge, MA: Harvard University Press.

Cohen, Wesley M. and Daniel A. Levinthal. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 35: 128-152.

Coleman, James S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94: 95-120.

Cook, Karen S. (1977). Exchange and power in networks of inter-organisational relations. *The Sociological Quarterly*, 18: 62-82.

Cox, D.R. and V. Isham. (1980). Point Processes. London: Chapman and Hall.

Davis, Gerald F. (1991). Agents without principles? The spread of the poison pill through the inter-corporate network. *Administrative Science Quarterly*, 36: 583-613.

Debackere, K., Clarysse, B. and M. A. Rappa. (1993). The application of sociometric and event-history modelling to bibliometric data: the case of transgene plants. *Research Evaluation*, 3 (1): 2-12.

Debackere, K. and M.A. Rappa. (1994). Technological communities and the diffusion of knowledge: a replication and validation. *R&D Management*, 24 (4): 355-371.

DiMaggio, Paul J. and Walter W. Powell. (1983). The iron cage revisited: institutional isomorphism and collective rationality in organisational fields. *American Sociological Review*, 48 (2):147-160.

Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11: 147-162.
Emery, F.E. and E.L. Trist. (1973). Towards a Social Ecology. New York: Plenum.
Encaoua, Daniel, and A. Jacquemin. (1980). Degree of monopoly, indices of concentration and threat of entry. *International Economic Review*, 21: 87-105.
Freeman, J. and S. Barley. (1990). The strategic analysis of inter-organisational relations in biotechnology. In R. Loveridge and M. Pitt (eds.) The Strategic Management of Technological Innovation. London: John Wiley & Sons.
Freeman, Linton C., Stephen P. Borgatti and Douglas R. White. (1991). Centrality in valued graphs: a measure of betweenness based on network flow. *Social Networks*, 13: 141-154.
Freeman, Linton C. (1979). Centrality in social networks: conceptual clarification. *Social Networks*, 1: 215-239.
Friedkin, Noah E. (1991). Theoretical foundations for centrality measures. *American Journal of Sociology*, 96 (6):1478-1504.
Garud, Raghu and Andrew H. Van de Ven. (1989). Technological innovation and industry emergence : the case of cochlear implants. In Andrew H. Van de Ven and Harold L. Angle and Marshall Scott Poole (eds.) Research on the Management of Innovation: 489-532. New York, NY: Harper and Row.
Granovetter, Mark S. (1985). Economic action and social structure: the problem of embeddedness. *American Journal of Sociology*, 91 (3):481-510.
Granovetter, Mark S. (1973). The strength of weak ties. *American Journal of Sociology*, 78 (6): 1360-1381.
Gray, Barbara. (1985). Conditions facilitating inter-organisational collaboration. *Human Relations*, 38 (10):911-936.
Greene, William H. (1992). LIMDEP Version 6.0 : User's Manual and Reference Guide. Bellport, NY: Econometric Software.
Grierson, Daniel (ed.). (1991). Plant Genetic Engineering. London: Chapman and Hall.
Hannan, Michael T. and Glenn R. Carroll. (1992). Dynamics of Organisational Populations: Density, Legitimation and Competition. Oxford: Oxford University Press.
Hannan, Michael T. and John Freeman. (1977). The population ecology of organisations. *American Journal of Sociology*, 82 (5):929-964.
Hannan, Michael T. and John Freeman. (1989). Organisational Ecology. Cambridge, MA: Harvard University Press.
Hannan, Michael T. (1986). A Model of Competitive and Institutional Processes in Organisational Ecology. Technical Report 86-13. Department of Sociology, Cornell University.
Hatten, Kenneth J. and May Louise Hatten. (1987). Strategic groups, asymmetrical mobility barriers and contestability. *Strategic Management Journal*, 8: 329-342.
Haveman, Heather A. (1993). Follow the leader : mimetic isomorphism and entry into new markets. *Administrative Science Quarterly*, 38 (4):593-627.
Jarillo, J. Carlos. (1988). On strategic networks. *Strategic Management Journal*, 9: 31-41.
Kamien, M.I. and N.L. Schwartz. (1982). Market Structure and Innovation. Cambridge, UK: Cambridge University Press.
King, Gary. (1988). Statistical models for political science event counts: bias in conventional procedures and evidence for the exponential Poisson regression model. *American Journal of Political Science*, 32 (3): 838-863.
Knoke, David and James H. Kuklinski. (1983). Network Analysis. Newbury Park: Sage Publications (28), fifth printing.
Larson, Andrea. (1992). Network dyads in entrepreneurial settings: a study of the governance of exchange relations. *Administrative Science Quarterly*, 37(1):76-104.
Nelson, Richard R. and Sidney G. Winter. (1982). An Evolutionary Theory of Economic Change. Cambridge, Mass.: Harvard University Press.
Nelson, Richard R. (1990). Capitalism as an engine of progress. *Research Policy*, 19: 193-214.

Nohria, Nitin and Robert G. Eccles. (1992). Face-to-face: making network organisations work. In N. Nohria and R.G. Eccles (eds.) Networks and Organisations. Boston, MA: Harvard Business School Press.
Pfeffer, Jeffrey and Gerald R. Salancik. (1978). The External Control of Organisations: A Resource Dependence Perspective. New York: Harper & Row.
Pisano, Gary P., Weijan Shan and David Teece. (1988). Joint ventures and collaboration in the biotechnology industry. In D.C. Mowery (ed.) International Collaborative Ventures in US Manufacturing. Cambridge, MA: Ballinger Publishing Co.
Pisano, Gary P. (1990). The R&D boundaries of the firm: an empirical analysis. *Administrative Science Quarterly*, 35: 153-176.
Powell, Walter W. (1990). Neither market nor hierarchy: network forms of organisation. In Barry M. Staw and L.L. Cummings (eds.) Research in Organisational Behaviour, 12:295-336. Greenwich, CT: JAI Press.
Provan, Keith G. (1993). Embeddedness, interdependence and opportunism in organisational supplier-buyer networks. *Journal of Management*, 19 (4): 841-856.
Rappa, Michael A. and Koenraad Debackere. (1992). Technological communities and the diffusion of knowledge. *R&D Management*, 22 (3): 209-221.
Schon, D.A. (1971). Beyond the Stable State. London: Temple Smith.
Scott, W. Richard. (1992). Organisations: Rational, Natural and Open Systems. Englewood Cliffs, NJ: Prentice Hall.
Snow, Charles C., Raymond E. Miles and H.J. Coleman. (1992). Managing the 21st century network organisation. *Organisational Dynamics*, 5-21.
Thorelli, Hans B. (1988). Networks: between markets and hierarchies. *Strategic Management Journal*, 7: 37-51.
Tirole, Jean. (1988). The Theory of Industrial Organisation. Cambridge, MA: The MIT Press.
Tuma, Nancy Brandon and Michael T. Hannan. (1984). Social Dynamics : Models and Methods. New York, NY: Academic Press.
Tushman, Michael L. and Philip Anderson. (1986). Technological discontinuities and organisational environments. *Administrative Science Quarterly*, 31: 439-465.
Useem, M. (1984). The Inner Circle. New York, NY: Oxford University Press.
Van de Ven, Andrew H., S. Venkataraman, Douglas Polley and Raghu Garud. (1989). Processes of new business creation in different organisational settings. In Andrew H. Van de Ven, Harold L. Angle and Marshall Scott Poole (eds.) Research on the Management of Innovation, 221-297. New York, NY: Harper & Row.
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5 (2): 171-180.
Williamson, O.E. (1991). Comparative economic organisation: the analysis of discrete structural alternatives. *Administrative Science Quarterly*, 36 (2): 269-296.
Wholey, Douglas R. and Susan M. Sanchez. (1991). The effects of regulatory tools on organisational populations. *Academy of Management Review*, 16 (4): 743-767.

FIGURE 1: Yearly number of organisational entries in plant biotechnology

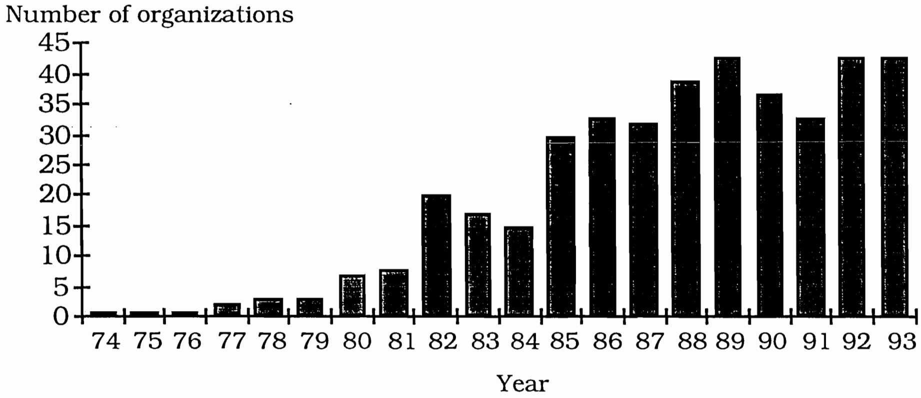

FIGURE 2: End-of-year density in plant biotechnology

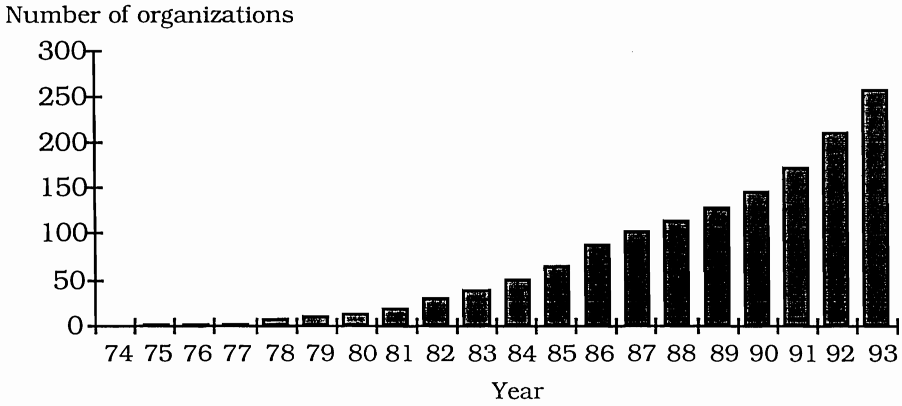

TABLE 1: Descriptive statistics on the variables

Plant biotechnology research (N=411)

VARIABLES:	MEAN	STAND. DEV.	LOWEST VALUE	HIGHEST VALUE
Control variables:				
Cum. Publication Volume:	377.32	514.72	1	1792
Date of Entry:	40.48	23.25	1	80
Market Growth Rate (%):	0.90	1.36	0	5.37
Density variables:				
Density:	74.47	75.98	1	270
$\text{Density}^2/1000$:	11.25	17.63	0.001	72.9
Network variables:				
Network clique ratio:	0.26	0.25	0	0.70
Centrality concentration:	-3.21	1.13	-4.99	-2.03

TABLE 2: The entry of research organisations into plant biotechnology

	POISSON REGRESSION MODEL					NEGATIVE BINOMIAL REGRESSION		
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 1	Step 2	Step 3
Control variables:								
Cum. publication volume	-0.0006** (0.0002)	-0.0013* (0.0006)	-0.0005 (0.0007)	-0.0011^{+} (0.0006)	-0.0001 (0.0007)	-0.0006** (0.0002)	-0.0013 (0.0008)	-0.0011 (0.0009)
Entry period	0.0394** (0.0019)	0.0131 (0.0080)	0.0143^{+} (0.0082)	0.0635** (0.0208)	0.0799** (0.0227)	0.0394** (0.0018)	0.0131^{+} (0.0073)	0.0634* (0.0249)
Market growth (%)	0.0747 (0.0499)	0.0975^{+} (0.0520)	0.0256 (0.0583)	0.1029* (0.0522)	0.0205 (0.0586)	0.0747 (0.0887)	0.0975 (0.0700)	0.1029 (0.0732)
Density variables:								
Density		0.0217** (0.0065)	0.0273** (0.0069)	0.0147* (0.0069)	0.0187** (0.0072)		0.0217** (0.0064)	0.0147* (0.0071)
Density^2/1000		-0.0382** (0.0147)	-0.0603** (0.0165)	-0.0342** (0.0146)	-0.0584** (0.0163)		-0.0382* (0.0181)	-0.0342* (0.0183)
Network variables:								
Network clique ratio			-1.7572** (0.5273)		-2.0263** (0.5218)			
Centrality concentr.				0.5513** (0.2177)	0.7120** (0.2384)			0.5513* (0.2693)
Constant						0.0090 (0.0376)	0.0092 (0.0357)	0.0150 (0.0367)
LOG-LIKELIHOOD	-170.67	-164.29	-158.93	-160.35	-153.13	-170.49	-164.16	-160.11

Notes:
1.Models are estimated by the Poisson Regression module in LIMDEP.
2.Number of observation intervals=80; number of entries=411.
3.Significance: $^{+}$: 0.05<p<0.1; *: 0.01<p<0.05; **: p<0.01; 1-tailed for independent variables, 2-tailed for control variables.
4.Standard errors of estimates between parentheses.